



NORTH-HOLLAND

A Fast Algorithm for Generalized Hankel Matrices Arising in Finite-Moment Problems

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Submitted by Ludwig Elsner

ABSTRACT

Consider an $n \times n$ lower triangular matrix L whose $(i + 1)$ st row is defined by the coefficients of the real polynomial $p_i(x)$ of degree i such that $\{p_i(x)\}$ is a set of orthogonal polynomials satisfying a standard three-term recurrence relation. If H is an $n \times n$ real Hankel matrix with nonsingular leading principal submatrices, then $\hat{H} = LHL^T$ will be referred to as a strongly nonsingular Hankel matrix with respect to the orthogonal polynomial basis $\{p_i(x)\}$. In this paper we develop an efficient $O(n^2)$ algorithm for the solution of a system of linear equations with a real symmetric coefficient matrix \hat{H} which is a Hankel matrix with respect to a suitable orthogonal polynomial basis. This leads to an efficient method for computing polynomial approximations of an unknown function given its modified moments. © 1997 Elsevier Science Inc.

1. INTRODUCTION

In this article we present a new, efficient algorithm for the solution of a linear system with a real symmetric coefficient matrix \hat{H}_{n-1} which is a strongly nonsingular Hankel matrix with respect to an orthogonal polynomial

*Supported by 40% funds of the Progetto Analisi numerica e matematica computazionale di MURST and by G.N.I.M. of C.N.R.

basis. This means that $\hat{H}_{n-1} = L_{n-1}H_{n-1}L_{n-1}^T$, where $H_{n-1} = (h_{i+j-2})$ is an $n \times n$ real strongly nonsingular Hankel matrix and $L_{n-1} = (l_{i,j})$ is a real $n \times n$ lower triangular matrix such that the polynomials $p_{i-1}(x) = (l_{i,1}, \dots, l_{i,i})(1, x, \dots, x^{i-1})^T$ satisfy a three-term recurrence

$$p_0(x) = \alpha_0, \quad p_1(x) = \alpha_1 x - \beta_1,$$

$$p_i(x) = (\alpha_i x - \beta_i)p_{i-1}(x) - \gamma_{i-1}p_{i-2}(x),$$

with $\alpha_{i-1} > 0$ and $\gamma_i > 0$ for $i \geq 1$.

Hankel matrices with respect to an orthogonal polynomial basis appear naturally in the solution of some finite weighted Hausdorff moment problems (see [12], [17], and [19] for general references). Specifically, we are interested in a modified weighted finite-moment problem which consists in solving the following first-kind integral equation:

$$Mf = \mu = (\mu_1, \dots, \mu_n)^T,$$

$$(Mf)_k = \int_0^1 p_{k-1}(x)f(x)w(x)dx, \quad k = 1, \dots, n,$$

where the polynomials $p_{k-1}(x)$ are the orthonormal Legendre polynomials in $[0, 1]$ [1]. These polynomials satisfy the following three-term recurrence relation:

$$p_0(x) = 1, \quad p_1(x) = 2\sqrt{3}x - \sqrt{3},$$

$$p_{i+1}(x) = \frac{(2i+1)\sqrt{2i+3}}{(i+1)\sqrt{2i+1}}(2x-1)p_i(x) - \frac{i\sqrt{2i+3}}{(i+1)\sqrt{2i-1}}p_{i-1}(x).$$

The vector μ is the known vector of the modified moments, $w(x)$ is a positive weight on $[0, 1]$, and $f(x)$ is an unknown function. Now, if we are looking for a polynomial approximation

$$f_k(x) = \sum_{i=0}^k f_i^{(k)} p_i(x), \quad k = 0, \dots, n-1,$$

of $f(x)$, then we find that the vectors $f_k = (f_0^{(k)}, \dots, f_k^{(k)})^T$ are the solution of the following linear systems

$$\hat{H}_k f_k = (\mu_1, \dots, \mu_{k+1})^T, \quad k = 0, \dots, n-1. \quad (1.1)$$

The matrix \hat{H}_k has the form of a modified Hankel matrix, that is,

$$\hat{H}_k = L_k H_k L_k^T = (h_{i,j}), \quad h_{i,j} = \int_0^1 p_{i-1}(x) p_{j-1}(x) w(x) dx,$$

where H_k is the $(k+1) \times (k+1)$ leading principal submatrix of the n th order positive definite Hankel matrix H_{n-1} with the classical moments

$$\int_0^1 x^{i+j-2} w(x) dx$$

of $w(x)$ along its antidiagonals; moreover, L_k is the $(k+1) \times (k+1)$ lower triangular matrix defined by the coefficients of the orthonormal Legendre polynomials $p_i(x)$ on $[0, 1]$. It is well known that L_k is the lower triangular factor of the Cholesky decomposition of the inverse of the Hilbert matrix of order $k+1$ [19].

The matrix H_k is usually ill conditioned even for small values of k [20], so that the solution of a linear system with coefficient matrix H_k should be avoided. However, in [4] D. Fasino proved that L_k is a good preconditioner for H_k in the sense that

$$\text{cond}(\hat{H}_k) = \text{cond}(L_k H_k L_k^T) < \frac{2k+1}{l}, \quad \inf_{x \in [0, 1]} w(x) = l > 0,$$

where $\text{cond}(A)$ represents the spectral condition number of the matrix A , that is, the ratio between its largest and its smallest singular value. This motivates the search for numerical methods which compute a triangular factorization of the matrix \hat{H}_{n-1} by avoiding any transition to the matrix H_{n-1} , or equivalently, by avoiding the transition from the modified moment problem to the classical moment problem.

The derivation of the new algorithm relies on a general approach to the solution of linear systems with structured coefficient matrices (see [8], [9], [14], and [15]). An anonymous referee pointed out that the approach of [14] had already been applied in [13] to devise a fast algorithm for Hankel matrices represented in orthogonal polynomial bases.

First, we introduce a suitable displacement operator $\mathcal{K}: R^{n \times n} \rightarrow R^{n \times n}$ having the form

$$\mathcal{K}(X) = T_n X - X T_n^T,$$

where T_n is a real tridiagonal matrix associated with the sequence $\{p_i(x)\}$. This matrix has the property that the characteristic polynomial of its left $i \times i$ principal submatrix T_i coincides with the monic polynomial associated with $p_i(x)$, that is,

$$\det(xI - T_i) = \frac{p_i(x)}{\alpha_0 \alpha_1 \cdots \alpha_i}.$$

Since $\mathcal{K}(\hat{H}_{n-1})$ is a rank-two matrix, we are then able to construct recursively the vectors ρ_i which satisfy $\hat{H}_{i-1}^{-1} e_i = \rho_i$, where e_i denotes the last column of the $i \times i$ identity matrix. The resulting algorithm, which will be presented in Section 2, takes $5.5n^2 + O(n)$ multiplications (divisions) and $O(n)$ storage. Moreover, it can be applied without ever explicitly forming the matrix \hat{H}_{n-1} , since we need only the first and the last two columns of the matrix \hat{H}_{n-1} for starting with the recursions. In this way, by using the well known expansion of $p_i(x)p_j(x)$ in terms of the same $p_i(x)$ [11], the needed $O(n)$ entries of the matrix \hat{H}_{n-1} can be determined at the overall cost of $O(n^2)$ arithmetic operations whenever we know the expansion of $w(x)$ in terms of the orthonormal Legendre polynomials. Finally, the solution of the equation $\hat{H}_{n-1}x = b$ can be obtained as soon as the vectors ρ_i , $i = 1, \dots, n$, are found at the overall computational cost of $6.5n^2 + O(n)$ multiplications and $O(n)$ storage.

2. DERIVATION OF THE ALGORITHM

Let us consider a nonsingular Hankel matrix

$$H_{n-1} = \begin{pmatrix} h_0 & h_1 & \cdots & h_{n-1} \\ h_1 & & \ddots & h_n \\ \vdots & \ddots & \ddots & \vdots \\ h_{n-1} & h_n & \cdots & h_{2n-2} \end{pmatrix}, \quad (2.1)$$

where we assume that $\det H_k \neq 0$ for all k , $0 \leq k \leq n-1$, i.e., H_{n-1} is a strongly nonsingular Hankel matrix.

Let $\{p_k(x)\}$ be a polynomial sequence such that $p_k(x)$ is a real polynomial of degree k which satisfies a three-term recurrence

$$p_0(x) = \alpha_0, \quad p_1(x) = \alpha_1 x - \beta_1, \quad (2.2)$$

$$p_k(x) = (\alpha_k x - \beta_k) p_{k-1}(x) - \gamma_{k-1} p_{k-2}(x) \quad (2.3)$$

with $\alpha_{k-1} > 0$ and $\gamma_k > 0$ for $k \geq 1$. It is well known that $p_k(x)$ are orthogonal polynomials with respect to a suitable scalar product $\langle \cdot, \cdot \rangle$; moreover, they coincide with the appropriately normalized characteristic polynomials of the leading principal submatrices of a real tridiagonal matrix T_n , that is,

$$\det(xI - T_k) = \frac{p_k(x)}{\alpha_0 \alpha_1 \cdots \alpha_k}, \quad k \geq 1,$$

where

$$T_k = \begin{pmatrix} \frac{\beta_1}{\alpha_1} & \frac{1}{\alpha_1} & & & \\ \frac{\gamma_1}{\alpha_2} & \frac{\beta_2}{\alpha_2} & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \frac{1}{\alpha_{k-1}} \\ & & & \frac{\gamma_{k-1}}{\alpha_k} & \frac{\beta_k}{\alpha_k} \end{pmatrix}.$$

The matrix T_n reduces to a symmetric one if the condition $\langle p_i(x), p_i(x) \rangle = \langle p_j(x), p_j(x) \rangle$ holds for any i and j . This condition is clearly satisfied when $p_i(x)$ are orthonormal polynomials.

Let us denote by L_k the $(k+1) \times (k+1)$ lower triangular matrix such that

$$L_k(1, x, \dots, x^k)^T = (p_0(x), \dots, p_k(x))^T.$$

It can be easily seen that

$$L_{n-1}^{-1} T_n L_{n-1} = F(p_n),$$

where

$$F(u) = \begin{pmatrix} 0 & 1 & & & \\ & \ddots & \ddots & & \\ & & 0 & 1 & \\ -\frac{u_0}{u_n} & \dots & \dots & -\frac{u_{n-1}}{u_n} \end{pmatrix}$$

represents the Frobenius matrix associated with the polynomial $u(x) = \sum_{i=0}^n u_i x^i$, $u_n \neq 0$.

In different contexts many authors [4, 6, 7, 13, 10, 18] have considered the problem of solving a linear system with a coefficient matrix which has the form of the modified Hankel matrix

$$\hat{H}_{n-1} = L_{n-1} H_{n-1} L_{n-1}^T.$$

Since H_{n-1} is nonsingular, then there exists an unique solution to the following linear system:

$$H_{n-1} (u_0^{(n)}, \dots, u_{n-1}^{(n)})^T = -(h_n, \dots, h_{2n-1})^T,$$

where h_{2n-1} is any number. If we write

$$u_n(x) = \sum_{i=0}^{n-1} u_i^{(n)} x^i + x^n,$$

then it has been proved [16] that

$$F(u_n) H_{n-1} = H_{n-1} F(u_n)^T. \quad (2.4)$$

By replacing

$$F(u_n) = F(p_n) - e_n \delta_n^T,$$

in (2.4) we find that

$$T_n \hat{H}_{n-1} - \hat{H}_{n-1} T_n^T = L_{n-1} \left[F(p_n) H_{n-1} - H_{n-1} F(p_n)^T \right] L_{n-1}^T,$$

which implies

$$T_n \hat{H}_{n-1} - \hat{H}_{n-1} T_n^T = L_{n-1} (e_n \delta_n^T H_{n-1} - H_{n-1} \delta_n e_n^T) L_{n-1}^T.$$

In this manner we obtain that

$$T_n \hat{H}_{n-1} - \hat{H}_{n-1} T_n^T = e_n \tilde{\delta}_n^T \hat{H}_{n-1} - \hat{H}_{n-1} \tilde{\delta}_n e_n^T,$$

or, equivalently,

$$\mathcal{A}(\hat{H}_{n-1}) = e_n \hat{\delta}_n^T - \hat{\delta}_n e_n^T. \quad (2.5)$$

On considering the $k \times k$ leading principal submatrix of $\mathcal{A}(\hat{H}_{n-1})$, $1 \leq k \leq n-2$, it follows that

$$T_k \hat{H}_{k-1} - \hat{H}_{k-1} T_k^T = \frac{1}{\alpha_k} \left[(\hat{h}_k, \dots, \hat{h}_{2k-1})^T e_k^T - e_k (\hat{h}_k, \dots, \hat{h}_{2k-1}) \right],$$

where e_k denotes the last column of the $k \times k$ identity matrix. Hence, we can write

$$\hat{H}_{k-1}^{-1} T_k - T_k^T \hat{H}_{k-1}^{-1} = \frac{1}{\alpha_k} \hat{H}_{k-1}^{-1} \{ r_k e_k^T - e_k r_k^T \} \hat{H}_{k-1}^{-1}, \quad (2.6)$$

where we set $r_k = (\hat{h}_k, \dots, \hat{h}_{2k-1})^T$.

Now, let us introduce the vectors $\rho_k = (\rho_1^{(k)}, \dots, \rho_k^{(k)})^T$, $1 \leq k \leq n$, defined by

$$\hat{H}_{k-1}^{-1} e_k = \rho_k.$$

Our recursive procedure for computing the vectors ρ_k , which define a triangular factorization of \hat{H}_{n-1} , relies on the following proposition.

PROPOSITION 2.1. *For $1 < k < n$ the vectors ρ_{k+1} satisfy the following recursions:*

$$\begin{aligned} & \frac{1}{\alpha_k} \frac{\rho_k^{(k)}}{\rho_{k+1}^{(k+1)}} (\rho_1^{(k+1)}, \dots, \rho_k^{(k+1)})^T - \frac{1}{\alpha_{k-1}} (\rho_{k-1}^T, 0)^T \\ &= \left(\frac{1}{\alpha_{k-1}} a_k - \frac{\beta_k}{\alpha_k} + \frac{1}{\alpha_k} \frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} + T_k^T \right) \rho_k, \end{aligned}$$

where a_k is given by

$$e_k^T \hat{H}_{k-1} (\rho_{k-1}^T, 0)^T = a_k.$$

Proof. From

$$\hat{H}_k^{-1} \frac{e_{k+1}}{\rho_{k+1}^{(k+1)}} = \left(\frac{\rho_1^{(k+1)}}{\rho_{k+1}^{(k+1)}}, \dots, \frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}}, 1 \right)^T,$$

we obtain that

$$\hat{H}_{k-1}^{-1} r_k = - \left(\frac{\rho_1^{(k+1)}}{\rho_{k+1}^{(k+1)}}, \dots, \frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} \right)^T. \quad (2.7)$$

In the view of (2.6), this implies that

$$\hat{H}_{k-1}^{-1} T_k e_k - T_k^T \rho^{(k)} = \frac{1}{\alpha_k} \left(\frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} \rho_k - \frac{\rho_k^{(k)}}{\rho_{k+1}^{(k+1)}} (\rho_1^{(k+1)}, \dots, \rho_k^{(k+1)})^T \right).$$

Since we have

$$T_k e_k = \frac{\beta_k}{\alpha_k} e_k + \frac{1}{\alpha_{k-1}} (e_{k-1}^T, 0)^T, \quad k > 1,$$

we can write

$$\begin{aligned} & \frac{1}{\alpha_{k-1}} \hat{H}_{k-1}^{-1} (e_{k-1}^T, 0)^T + \frac{\beta_k}{\alpha_k} \rho_k - T_k^T \rho_k \\ &= \frac{1}{\alpha_k} \left(\frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} \rho_k - \frac{\rho_k^{(k)}}{\rho_{k+1}^{(k+1)}} (\rho_1^{(k+1)}, \dots, \rho_k^{(k+1)})^T \right). \end{aligned}$$

Replacing now $\hat{H}_{k-1}^{-1} (e_{k-1}^T, 0)^T$ by

$$\chi^{(k)} = (\rho_{k-1}^T, 0)^T - a_k \rho_k, \quad k > 1,$$

for a certain a_k , produces

$$\frac{1}{\alpha_k} \frac{\rho_k^{(k)}}{\rho_{k+1}^{(k+1)}} (\rho_1^{(k+1)}, \dots, \rho_k^{(k+1)})^T - \frac{1}{\alpha_{k-1}} (\rho_{k-1}^T, 0)^T \quad (2.8)$$

$$= \left(\frac{1}{\alpha_{k-1}} a_k - \frac{\beta_k}{\alpha_k} + \frac{1}{\alpha_k} \frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} + T_k^T \right) \rho_k, \quad k > 1. \quad (2.9)$$

Comparison of $\rho_k^T \hat{H}_{k-1} \chi^{(k)}$ and $\chi^{(k)T} \hat{H}_{k-1} \rho_k$ finally reveals that a_k is given by

$$a_k = - \frac{\rho_{k-1}^{(k)}}{\rho_k^{(k)}},$$

and therefore we may determine a_k by means of

$$e_k^T \hat{H}_{k-1} (\rho_{k-1}^T, 0)^T = a_k. \quad \blacksquare \quad (2.10)$$

In order to perform efficiently the computations (2.8)–(2.10), we may observe that the equality (2.8)–(2.9) can be rewritten in the following way:

$$\begin{aligned} & \left(\frac{1}{\alpha_{k-1}} a_k - \frac{\beta_k}{\alpha_k} + \frac{1}{\alpha_k} \frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} + T_n^T \right) \begin{pmatrix} \rho_k \\ 0 \end{pmatrix} \\ &= \frac{1}{\alpha_k} \frac{\rho_k^{(k)}}{\rho_{k+1}^{(k+1)}} \begin{pmatrix} \rho_{k+1} \\ 0 \end{pmatrix} - \frac{1}{\alpha_{k-1}} \begin{pmatrix} \rho_{k-1} \\ 0 \end{pmatrix}, \quad k > 1, \end{aligned}$$

where we extend the vector ρ_k to dimension n by adding zeros. For $k = 1$, we have

$$\left(-\frac{\beta_1}{\alpha_1} + \frac{1}{\alpha_1} a_2 + T_n^T \right) \begin{pmatrix} \rho_1 \\ 0 \end{pmatrix} = \frac{1}{\alpha_1} \frac{\rho_1^{(1)}}{\rho_2^{(2)}} \begin{pmatrix} \rho_2 \\ 0 \end{pmatrix}. \quad (2.11)$$

By means of (2.5), we find that

$$\begin{aligned} & \left(\frac{1}{\alpha_{k-1}} a_k - \frac{\beta_k}{\alpha_k} + \frac{1}{\alpha_k} \frac{\rho_k^{(k+1)}}{\rho_{k+1}^{(k+1)}} - e_n \hat{\delta}_n^T + T_n \right) \hat{H}_{n-1} \begin{pmatrix} \rho_k \\ 0 \end{pmatrix} \\ &= \frac{1}{\alpha_k} \frac{\rho_k^{(k)}}{\rho_{k+1}^{(k+1)}} \hat{H}_{n-1} \begin{pmatrix} \rho_{k+1} \\ 0 \end{pmatrix} - \frac{1}{\alpha_{k-1}} \hat{H}_{n-1} \begin{pmatrix} \rho_{k-1} \\ 0 \end{pmatrix}, \quad k > 1, \end{aligned}$$

and therefore we are able to compute the vectors $\hat{H}_{n-1}(\rho_k, 0)^T$ in a recursive way using only $O(n)$ storage, once we know the first and the last two columns of the matrix \hat{H}_{n-1} .

The resulting algorithm for determining the vectors ρ_k , $k = 1, \dots, n$, proceeds as follows:

ALGORITHM 1.

Input: the entries of the tridiagonal matrix T_n associated with the sequence of the real polynomials $p_i(x)$; the entries of the first and the last two columns of a real strongly nonsingular Hankel matrix \hat{H}_{n-1} with respect to the polynomial basis $\{p_i(x)\}$.

Output: the entries of the vectors ρ_k , $k = 1, \dots, n$, which satisfy $\hat{H}_{k-1}^{-1} e_k = \rho_k$.

Determine $\hat{\delta}$ by means of (2.5) (observe that its last entry can be chosen arbitrarily). Compute $\rho_1^{(1)} = 1/\hat{h}_{1,1}$ and ρ_2 by means of (2.11).

Compute recursively for $k = 2, \dots, n-1$:

1. evaluate a_{k+1} by means of (2.10);
2. find the vector $\rho_{k+1}/\rho_{k+1}^{(k+1)}$ by means of (2.8)–(2.9);
3. determine $\rho_{k+1}^{(k+1)}$ by means of $\hat{H}_k(\rho_{k+1}/\rho_{k+1}^{(k+1)}) = e_{k+1}/\rho_{k+1}^{(k+1)}$.

The number of multiplications and divisions performed at step k of Algorithm 1 is $11k + O(1)$. The initialization phase has the cost of $O(n)$ arithmetical operations. Therefore, the number of multiplications and divi-

sions in the whole algorithm is $5.5n^2 + O(n)$, and moreover it can be implemented using only $O(n)$ storage.

Algorithm 1 generalizes some well-known fast procedures for solving Hankel linear systems (see [5] and the references given there about Levinson-type algorithms for Hankel matrices). In fact, in the case where $\alpha_{i-1} = 1$, $\beta_i = 0$, and $\gamma_i = 0$, $i = 1, \dots, n$, then the corresponding polynomials (2.2)–(2.3) become just $p_i(x) = x^i$ —which do not constitute an orthogonal set—and, moreover, T_n reduces to the shift operator $P_n = (p_{i,j})$ with $p_{i,j} = \delta_{i,j-1}$.

Now the solution of the equation $\hat{H}_{n-1}x = b$, $b = (b_1, \dots, b_n)^T$, can be obtained from the following classical result [8].

PROPOSITION 2.2. *The matrix \hat{H}_{n-1} is strongly nonsingular if and only if the equations*

$$\hat{H}_{k-1} \rho_k = e_k, \quad k = 1, \dots, n,$$

are solvable. In this case $e_k^T \rho_k \neq 0$, $k = 1, \dots, n$. Moreover, if the vectors z_k are defined recursively by means of

$$\begin{aligned} z_1 &= b_1 / \hat{h}_{11}, \\ \eta_k &= b_k - e_k^T \hat{H}_{k-1} (z_{k-1}^T, 0)^T, \\ z_k &= (z_{k-1}^T, 0)^T + \eta_k \rho_k, \end{aligned}$$

then we find that $\hat{H}_{n-1} z_n = b$.

The above recursions take $n^2 + O(n)$ multiplications, and therefore we are able to solve a linear system with coefficient matrix \hat{H}_{n-1} at the overall computational cost of $6.5n^2 + O(n)$ multiplications (divisions) and $O(n)$ storage.

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